Audience measurement of digital signage: Quantitative study in real-world environment using computer vision

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Abstract

We present a quantitative study of digital signage audience measurement using computer vision. We developed a camera enhanced digital signage display that acquires audience measurement metrices with computer vision algorithms. Temporal metrices of person's dwell time, display in-view time, and attention time are extracted. The system also determines demographic metrices of gender and age group. The digital signage display was deployed in a real world environment of a clothing boutique, where demographic and viewership data of 1294 persons ensemble was recorded, manually verified and analysed. Analysis shows that 35% of ensemble specifically *looked-at* the display, having the average attention time of 0.7s. Interestingly, the attention time was substantially higher for men (1.2s) as for women (0.4s). Age group comparison reveals that youth (1-14 years) are the most responsive to the digital signage. Finally, the analysis shows that the average attention time is significantly higher when displaying the dynamic content (0.9s) as compared to the static content (0.6s).

Keywords: digital signage, audience measurement, computer vision, quantitative study

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1. Introduction

Modern applications of digital signage are interfaces to public and internal information, advertising, brand building, and making enhanced customer experience [1, 2, 3, 4, 5]. Digital signage displays have the advantage over static signs because they can display multimedia content such as images, animations, video and audio. The content can be adapted in real time to a different context and audience, making it attractive for use at airports, hotels, universities, retail stores, and various outdoor public spaces. However, frequently, the displayed content is generic and uninteresting for observers causing the effect of *Display Blindness* [6]. In order for digital signage to become effective as the information interface, the displayed content should be informative, dynamic, and attractive.

The actual attention that people pay to public displays is one of the key parameters of digital signage. Comparative case study of Huang et al [7] reveals that paying attention to public displays is a complex process, which depends on several criteria such as positioning, display size, content format and dynamics. In order for digital signage to maximise the attention, these should be considered already during the design phase of the digital signage system. Research in digital signage today is aimed at exploring designs and options for delivering *engaging and interactive* content in public places [8]. Various interaction modalities are proposed, including body position, speech, facial expression, body posture, gaze, touch [9]. Chen et al describe a prototype system for interaction with digital signage using hand gestures [10]. Also, adaptive and interactive digital signage is permeating urban life and architecture [11] as well as ubiquitous computing [3]. However, ubiquitous monitoring [12] can lead to negative responses. Little et al address the problem of receiving personal information in public spaces via personalized interaction [13].

Digital signage can yield a remarkable impact in commerce. A generalization study by Burke [14, 15] reveals that in-store digital signage increases customer traffic and sales. Indeed, the shoppers are the most responsive to messages that relate to the task at hand and their immediate interest. Qualitative study using questionnaires by Dennis at al [16] shows that digital signage is an effective stimulus, adding to positive perceptions of the mall environment, the emotions, and the approach behaviour. Finally, digital signage screens also improve the image of shopping malls and create a favourable shopping atmosphere [17]. Digital signage clearly is a strong contributor in various process and fields; however, most of the measured impact is qualitative, using interviews and questionnaires. Therefore, envisaging a *quantitative* method, with means for determining various audience measurement metrices could open a completely new window to digital signage, allowing for maximum interaction, context-awareness, and self-motivated augmented learning [17].

In this paper, we present a computer vision enhanced digital signage system for monitoring actual activity of the audience in front of the system and collect quantitative data, including audience measuring and demographic metrices of person's dwell time, display in-view time, attention time, gender, and age group. This approach gives a direct quantitative insight into the digital signage audience measurement. To demonstrate the actual performance of the system, we perform a quantitative study in real-world environment of a clothing boutique. Collected data can be used for behavioral analysis of customers. The outline of the paper is as follows: Section 2 presents audience measurement metrices and the computer vision enhanced digital signage system, Section 3 elaborates the audience measurement field study, Section 4 presents experiment results, and Section 5 gives final conclusions.

2. Computer vision enhanced digital signage

Real-time audience measurement system is developed for application in digital signage. It is based on computer vision methods of detecting and tracking persons' faces from video that is captured by a digital camera which accompanies the digital signage screen. Further, the system automatically performs analysis of various metrices and generates quantitative statistics of the detected persons. Temporal and demographic audience measurement metrices are collected: (i) dwell time describes the sum of all time intervals when observer was present in the same room or area as the display, (ii) in-view time represents the duration of all time intervals when observer had the display screen in his field of view (without necessarily paying attention to the screen), (iii) attention time is part of the in-view time when observer is actually looking at the display, and (iv) gender and age group are demographic characteristics of each individual. Four video analysis modules are designed in our digital signage system, each for the determination of one of the metrices. Figure 1 illustrates the scheme of video analysis modules. Below, we separately present each module and comment on aspects of privacy.

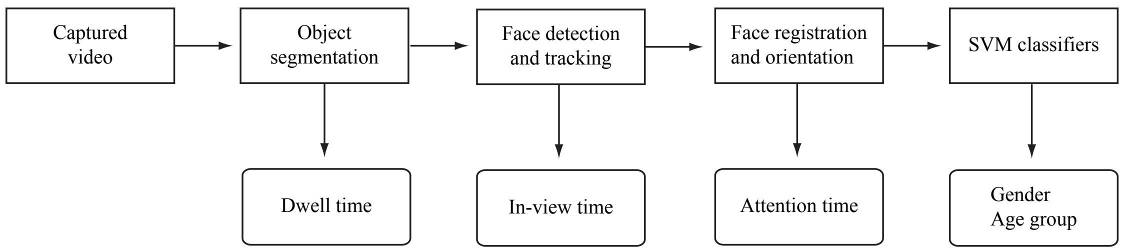

Figure 1: Scheme of computer vision enhanced digital signage.

2.1. Dwell time

Object segmentation is used to determine dwell time of each observer that enters the store. We employ a background subtraction algorithm to extract foreground regions of captured image and define potential presence of observers. Since the camera is static we use a Mixture of Gaussians based background modeling [18]. Each image pixel is characterized by its intensity value in RGB space. The results of typical foreground subtraction are illustrated in Figure 2b.

Figure 2: Object segmentation. a) Typical input image. b) Image after object segmentation using background subtraction.

The segmented regions are tracked using Fast Match Template algorithm supplied in OpenCV library [19]. This template matching algorithm is adapted for real-time video processing. The upper body part of an observer is used as a template image.

2.2. In-view time

Face detection algorithm is used to determine whether observers are facing the display. We use frontal and profile Viola & Jones face detector [20] that runs in real-time. The hit rate of this face detection method is reported to be 98% which is suitable for our purposes in terms of detection accuracy and speed. Using this face detector we get the location of present faces regardless of their position and scale down to the size of 20x20 pixels.

2.3. Attention time

Orientation of the observers head is the central parameter in the determination of the attention time (when the observer is actually looking at the display). We use the multi-view Active Appearance Model (AAM) method to register the observer's face. The AAM simultaneously models the intrinsic variation in shape and texture of a deformable visual object as a linear combination of basis modes of variation [21]. Although linear in both shape and appearance, overall, AAMs are nonlinear parametric models in terms of the pixel intensities. Fitting an AAM to an image consists of minimizing the error between the input image and the closest model instance; i.e. solving a nonlinear optimization problem [22]. Using multi-view AAM registration we estimate observer's head orientation and denote his attention.

2.4. Gender and age group classifiers

The demographic metric of age and gender is determined within 7 age groups: 1-14, 15-24, 25-34, 35-44, 45-54, 55-64, and over 65 years, all either male or female. We apply Support Vector Machine (SVM) machine learning algorithm for the age and gender classification. The FERET database [23] is used as a learning set for gender and age classifiers. Database comes fully annotated including facial images and corresponding gender and year of birth data for 856 individuals. We use the AAM facial registration method described in Section 2.3 to register a face and warp it to the normalized frontal form of size 50x50px. Normalized FERET faces are used to train SVM classifiers for gender and age. Using this approach we achieve 91% classification accuracy on FERET testing set.

2.5. Aspects of privacy

Privacy-by-design [24, 25] as well as privacy-by-architecture [26] principles are incorporated in our computer vision enhanced digital signage system structure, to ensure secure and appropriate handling with the acquired personal data. By design, all image processing is performed by the display unit in real-time, therefore no visual records are stored or distributed over network. Display unit discards video image immediately after processing, storing only audience measurement metrices that are sent to the central server using encrypted data transfer. All customers in the shop are notified of the video-recording, in accordance with the national privacy legislation.

3. Field study

A field study was performed to assess our digital signage system in a real-world environment, specifically focusing on the attention of the observers, i.e. their time metrices. We used a 24' Sony Vaio VPCL135FX/B computer display enhanced with Logitech WebCam Pro 9000 camera. Camera's horizontal FOV is 63.1° and vertical FOV is 49.5°. Video was captured at 20 FPS using resolution of 800x600 pixels. The digital signage system was positioned into an clothing boutique in the city center of Ljubljana, Slovenia. The floor plan consisted of main area (approximately $35m^2$) situated between the entrance and the cashier's desk (see Figure 2a) with additional room in the back used for changing. We should mention that the shop sells higher fashion (higher prices) clothing and apparel, which can affect the demographic and behaviour characteristics.

Highest attention rates of our system were achieved by using criteria according to [6, 7]. To optimise the position, the display was situated at the eye-level height on a special shelf next to the cashier's desk, facing directly the entrance. For the eye-catching criterion, the shelves immediately next to the display were filled with small textile goods that were of immediate eye-catching interest. To record data for assessment of the animated content criterion, static and dynamic content types were displayed during the field study. The static content type comprised of a slide show with 20 slides and the time interval between slides of 10s. Slides showed pictures of distinctive sportsmen and sportswomen wearing attire from the shop's assortment. The dynamic content type comprised of three video clips, which showed various sports and entertainment situations. The slide show and the videos were designed also to maximise the colorful content criterion, emotional content criterion and aesthetic look criterion. Examples of broadcasting content are presented in Figure 3.

The study was performed within 23 daily sessions, of totally 214 hours, and acquired characteristics and attention responses of a sample of 1294 people. To ensure ecological validity all automatically collected data was

a) 

b) 

Figure 3: Broadcasting content. a) Static content type. b) Dynamic content type.

manually verified by two human reviewers. We devised a video annotation program for manual processing, following guidelines for effective video annotation proposed in [27]. Cohen's kappa coefficient κ was used for the evaluation of the inter-rater agreement [28]. We determine $\kappa_{gender} = 1.0$ for gender classification and $\kappa_{age\_group} = 0.91$ for estimating observers age groups.

We also perform a Kruskal-Wallis (K-W) test to determine the statistical significance of specific audience measurement metrices [29]. The K-W test is a non-parametric method for testing whether measured data originates from the same distribution. This method was chosen since it covers general (not necessarily normal) distributions, as observed in our extracted data.

Using manually verified data obtained from gender and age classifiers presented in Section 2.4, the system identified, that 61% of the acquired sample of customers were female and 39% were male. The age distribution was as follows: 7% in 1-14 years, 10% in 15-24 years, 20% in 25-34 years, 25% in 35-44 years, 19% in 45-54 years, 12% in 55-64 years and 7% in 65+ years group. Full presentation of age and gender structure of the acquired sample is presented in Figure 4.

Finally, we would like to comment that, in the pre-processing phase, all retail personnel audience data was excluded. In addition to the original data the system identified also 12 outliers, i.e. people whose dwell, in-view or attention time was 30 times over the mean. Finding such out-of-average behaviour, which is beyond this paper, opens a new challenge to digital signage and could offer new information about the augmented learning.

4. Results

The full results of the analysis are presented in Table 1. Note, that the table summarises result of three general tests performed for the audience met-

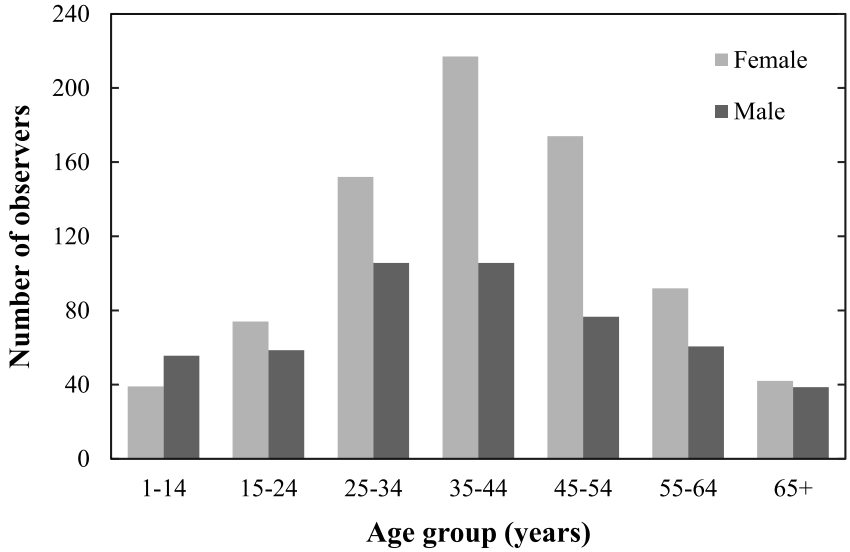

Figure 4: Distribution of observers considering age group and gender.

rics of gender, age group, and content. Further, for dwell, in-view, and attention time, the columns present: the number of analysed observers/customers (N), average dwell/in-view/attention time (Mean), and standard deviation of Mean (SD). Results of the two-tailed K-W test ($\alpha = 0.05$) are presented with: Mean rank, test result value (H), degrees of freedom (DF) and the representative p-value.

Table 1 shows large standard deviation in all dwell, in-view, and attention time, which interestingly implies strongly varying behaviour of shop customers. Indeed, some people stayed in the shop for less than 20s, whereas others were there for over half an hour, which expectably yields high standard deviation.

4.1. Dwell time

Overall mean of dwell time -time when person is in the same room as display- is 144s (see Table 1, row 13, column 5). On average, each observer re-entered the scene 1.8 times. More specifically, the distribution of dwell times for all observers is presented in Figure 5.

Comparison of mean dwell time for gender reveals that male shoppers have higher average mean dwell time (156 s) than women (137 s) (see Table 1, rows 2 and 3, column 5). Also, the K-W test confirms the significant

	Var.	Value	N	Mean	SD	Mean rank	H	DF	p
Dwell time	Gender	male	504	**156**	204	674.3	**4.25**	1	**0.039**
		female	790	**137**	193	630.4			
	Age group	1-14	95	148	186	631.3	**20.4**	6	**0.002**
		15-24	133	**101**	146	521.4			
		25-34	258	154	222	650.6			
		35-44	323	138	191	648.9			
		45-54	251	163	206	687.6			
		55-64	153	157	213	691.8			
		65+	81	124	158	650.4			
	Content	slides	665	141	193	635.1	1.48	1	0.223
		video	629	148	202	660.5			
	Overall		1294	**144**	198				
In-view time	Gender	male	504	**20.9**	27.7	721.5	**32.4**	1	**< 0.0001**
		female	709	**15.6**	22.6	600.3			
	Age group	1-14	95	17.9	26.7	654.7	6.77	6	0.343
		15-24	133	14.5	19.2	595.4			
		25-34	258	18.9	27.1	662.1			
		35-44	323	16.2	24.1	629.9			
		45-54	251	18.7	26.1	642.8			
		55-64	153	20.4	26.3	697.7			
		65+	81	15.7	18.3	667.8			
	Content	slides	665	16.7	22.7	637.6	0.85	1	0.357
		video	629	18.6	26.7	656.8			
	Overall		1294	**17.6**	24.8				
Attention time	Gender	male	504	**1.19**	2.61	741.7	**71.9**	1	**< 0.0001**
		female	790	**0.42**	1.19	587.4			
	Age group	1-14	95	**2.39**	4.54	**815.1**	**37.6**	6	**< 0.0001**
		15-24	133	0.70	1.41	663.6			
		25-34	258	0.60	1.35	638.2			
		35-44	323	0.42	1.19	589.7			
		45-54	251	0.67	1.69	647.5			
		55-64	153	0.68	1.73	659.9			
		65+	81	0.66	1.29	660.9			
	Content	slides	665	**0.60**	1.49	625.8	**5.71**	1	**0.017**
		video	629	**0.86**	2.27	670.4			
	Overall		1294	**0.72**	1.91				

Table 1: Quantitative results of the digital signage audience measurement. Values of mean and standard deviation are given in seconds.

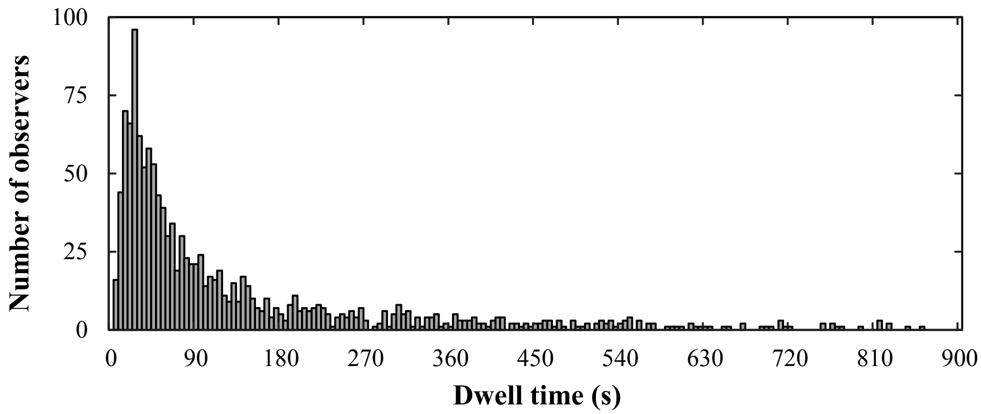

Figure 5: Distribution of dwell times for all observers.

difference in mean ranks distribution (H(1) = 4.25, p = 0.039). Age comparison shows that the age group of 15-24 years has mean dwell time substantially below average (101s as compared to average 144s). Difference in distribution is also confirmed using K-W test (H(5) = 20.4, p = 0.002). Indeed, this qualitatively characterises that the boutique aims at an older target age group, between 25 and 55 years; which is also evident from Figure 4. According to mean comparison and K-W test (H(1) = 1.48, p = 0.023) content type has no significant effect on the dwell time.

Interpreting the results, we could reason that the observed difference in distribution of dwell time between males and females is due to the difference in the number of short shopping visits. Indeed, there are 51% of all females and only 44% of all males that have dwell time below 60s.

4.2. In-view time

In-view time analysis shows that the display comes in the field of view of an average person 4.9 times. The corresponding average of total in-view time is 17.6s (see Table 1, row 25, column 5), indicating that the display was in the field of view of the average person (customer) for 12% of the total (dwell) time the person spent in room with the display. Distribution of the in-view time is presented in Figure 6.

Gender comparison reveals higher in-view time for males. Significant difference in distributions is also confirmed by the K-W test (H(1) = 32.4, p = < 0.0001. No significant effect on the in-view time is found for the

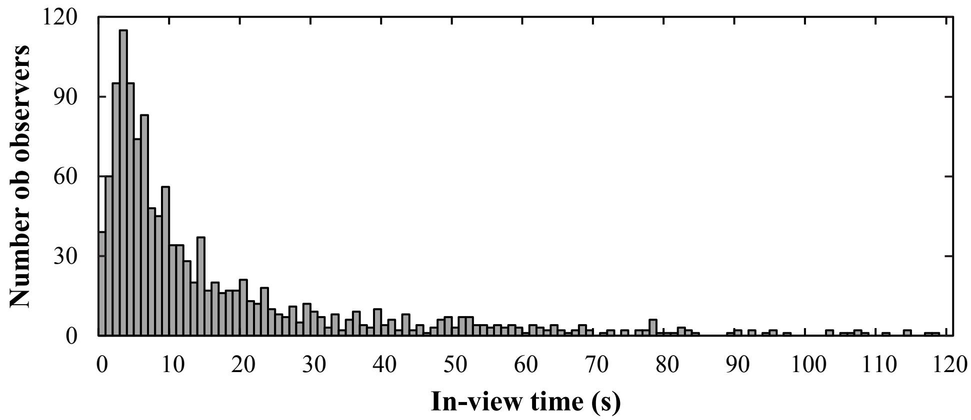

Figure 6: Distribution of in-view time for all observers.

metrices of age (H(5) = 6.77, p = 0.034) and displayed content (H(1) = 0.85, p = 0.357).

4.3. Attention time

The analysis reveals that 35% of all people entering the store looked at the display at least once, 12% looked at the display at least twice, and 6% three times or more. The corresponding total average attention time of an average person was 0.7s (see Table 1, row 37, column 5). Attention time distribution is presented in Figure 7.

Interestingly, males are more attracted to digital signage than females: 48% of all males and only 27% of all females looked at the display at least once. The overall average attention time for males was 1.2s and for females 0.4s (see Table 1, rows 26 and 27, column 5). Significant difference in distribution was also confirmed using K-W analysis (H(1) = 71.9, p = $<$ 0.0001).

The age group shows a strong impact on the attention time. K-W test shows significant difference in distributions (H(5) = 37.6, p = $<$ 0.0001). Observing evident difference in mean attention time for 1-14 age group (see Table 1, row 28, column 5), we perform two-tailed Steel-Dwass-Critchlow-Fligner multiple pairwise comparison post-hoc test [30] which confirms statistically significant difference between the 1-14 group and all the other age groups. We believe that the reason for the youngest age group being so distinctive is in shop goods. Retail assortment offered nearly only adult apparel.

Content type has no significant effect on dwell time and in-view time;

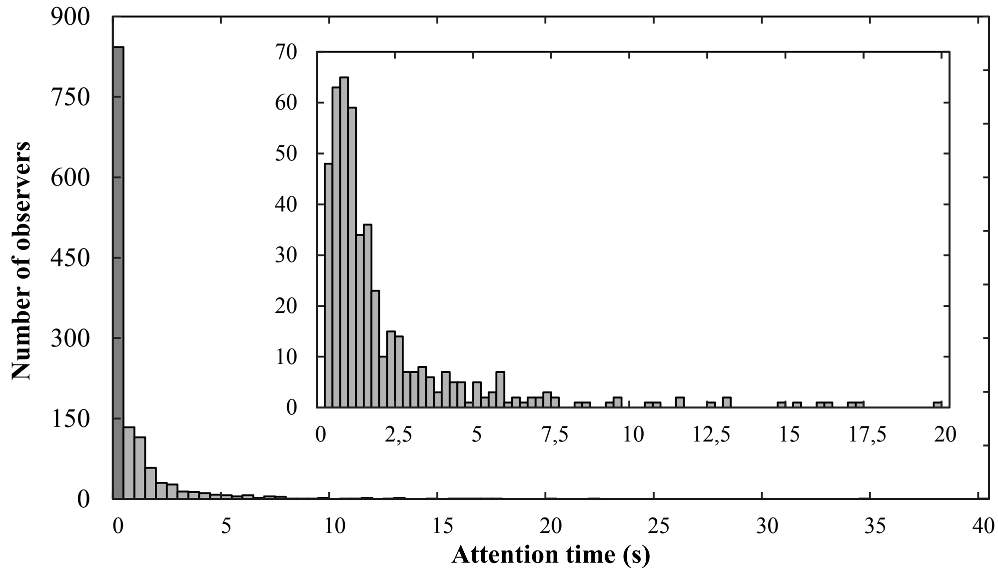

Figure 7: Distribution of attention time. The outer chart shows the distribution of overall attention time for all observers. The dark column represents the percentage of people that did not look at display at all (zero attention time). The inner chart illustrates the distribution of attention time for observers who looked at the display at least once.

however, it has an effect on the attention time (see Table 1, rows 35 and 36). The evaluation confirms that dynamic content draws ~ 1.5 times attention than static content. More specifically, the average attention time increased for 43% when broadcasting dynamic content. The results agree well with the qualitative digital signage observations [7, 6, 16] as well as with psychological studies on attention capture [31, 32]. Statistical significance was also validated using K-W test ($H(1) = 5.71$, $p = 0.017$).

4.4. Summary of analysis metrices by gender, age, and content type

Gender: Gender has a significant impact on all three observed temporal metrices. Men are more receptive for digital signage than women, having on average larger dwell time, in-view time, and attention time (see Table 1).
Age: Age has no effect on the in-view time; however, it affects dwell time and attention time. Youth group (1-14 years) demonstrates highest attention time, whereas age group of 35-44 shows lowest attention time.
Content: Content (static or dynamic) does not affect the dwell and in-view time. However, broadcasting dynamic content shows strong increase (43%)

in the attention time.

5. Conclusion

Advanced digital signage system is developed, based on the display screen, wide angle digital camera, and audience measurement software. Computer vision and machine learning methods are implemented for an automatic assessment of the audience measurement time and demographic metrices, including dwell time, in-view time, attention time, gender, and age. For all metrices individual computer program moduli are developed, that are transferable and could be used also in other software platforms.

The digital signage system is applied in a real-world-environment field study of the customer research in a clothing boutique, performing a full quantitative audience measurement study. The attention time quantifier reveals, that, on average, men pay attention to the digital signage display for 1.2s, whereas women only 0.4s. Age group comparison shows that attention time to digital signage is highest (2.4s) in the youth age group (1-14 years) as compared to the all average attention time of 0.7s. Interestingly, the average attention time is lowest in the 35-44 years age group (0.42s). The contents quantifier -dynamic or static-, shows that broadcasting dynamic and not static digital signage content increases attention time for 43%.

More generally, these results are aimed to improve the future design of digital signage systems, as well as their content. The developed system could serve as an advanced quantitative tool for various types of audience measurements. Finally, as steps towards maximum-impact digital signage, we propose future research on the role of the display position, display size, and all adaptive content.

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